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1 **Sub-seasonal forcing drives year-to-year variations of**
2 **Southern Ocean primary productivity**

3 **Channing J. Prend¹, M. G. Keerthi², Marina Lévy², Olivier Aumont², Sarah**
4 **T. Gille¹, Lynne D. Talley¹**

5 ¹Scripps Institution of Oceanography, University of California San Diego, La Jolla, CA, USA

6 ²Sorbonne Université, CNRS, LOCEAN-IPSL, Paris, France

7 **Key Points:**

- 8 • Year-to-year variations of annual mean chlorophyll in the Southern Ocean are weakly
9 correlated with the Southern Annular Mode
- 10 • Non-seasonal chlorophyll fluctuations are driven by intermittent sub-seasonal events,
11 which dominate the changes in the annual mean
- 12 • The spatial autocorrelation for the chlorophyll seasonal cycle is much larger than
13 for variations in the annual mean chlorophyll

Corresponding author: Channing J. Prend, cprend@ucsd.edu

Abstract

Primary productivity in the Southern Ocean plays a key role in global biogeochemical cycles. While much focus has been placed on phytoplankton production seasonality, non-seasonal fluctuations exceed the amplitude of the seasonal cycle across large swaths of the Antarctic Circumpolar Current. This non-seasonal variability comprises a broad range of timescales from sub-seasonal (<3 months) to multi-annual (>1 year), all of which can project onto the annual mean value. However, year-to-year variations of surface chlorophyll (SChl), a proxy for phytoplankton biomass, are typically attributed to ocean circulation changes associated with the Southern Annular Mode (SAM), which implicitly assumes that sub-seasonal variability averages to near-zero over long timescales. Here, we test this assumption by applying a timeseries decomposition method to satellite-derived SChl in order to separate the low-frequency and high-frequency contributions to the non-seasonal variability. We find that throughout most of the Southern Ocean, year-to-year SChl variations are dominated by the sub-seasonal component, which is not strongly correlated with the SAM. The multi-annual component, while correlated with the SAM, only accounts for about 10% of the total SChl variance. This suggests that changes in annual mean SChl are related to intermittent forcing at small scales, rather than low-frequency climate variability, and thus do not remain correlated over large regions.

Plain Language Summary

Microalgae called phytoplankton are the foundation of marine food webs and play a large role in the carbon cycle. Therefore, understanding the mechanisms that drive phytoplankton variability is of critical importance to marine ecosystems and global climate. Phytoplankton growth is known to exhibit a strong seasonal cycle. In addition to this, phytoplankton biomass also varies between years. This variability is often linked to multi-year climate oscillations like El Niño. On short timescales, phytoplankton are also influenced by processes such as storms and eddies, which alter the supply of nutrients and light that they need to grow. In this study, we use satellite measurements to untangle the different timescales of phytoplankton variability in the Southern Ocean, which surrounds Antarctica. We find that year-to-year fluctuations in phytoplankton biomass are driven by intermittent events associated with storms and eddies, rather than multi-year climate oscillations. Therefore, processes occurring at small scales must be considered

45 in order to understand long-term phytoplankton variability and trends related to climate
46 change.

47 **1 Introduction**

48 The Southern Ocean is a high-nutrient low-chlorophyll environment where phyto-
49 plankton growth is limited primarily by iron and light (Mitchell et al., 1991; de Baar et
50 al., 1995). Physical processes in the ocean impact these controls, subsequently affecting
51 the distribution of phytoplankton across a wide range of spatial and temporal scales (Lévy
52 et al., 2012; Rousseaux & Gregg, 2014; Ardyna et al., 2017; Rohr et al., 2017; Li et al.,
53 2021). Indeed, phytoplankton biomass, inferred from satellite-derived surface chlorophyll
54 (SChl), exhibits variability from sub-seasonal (<3 months) to multi-annual (>1 year)
55 timescales (Arrigo et al., 2008; Thomalla et al., 2011; Frenger et al., 2018; Keerthi et al.,
56 2020). Untangling these disparate scales is necessary to develop a quantitative model of
57 spatiotemporal chlorophyll variability and identify long-term trends associated with cli-
58 mate change, which are currently eclipsed by natural year-to-year variations in most re-
59 gions globally (Behrenfeld et al., 2006; Martinez et al., 2009; Henson et al., 2010; Gregg
60 & Rousseaux, 2019).

61 In the Southern Ocean, changes in annual mean SChl have been linked to the South-
62 ern Annular Mode (SAM), the leading mode of atmospheric variability in the Southern
63 Hemisphere (Thompson & Wallace, 2000). SAM influences the ocean circulation and strat-
64 ification in the region, which in turn impacts primary productivity by modulating nu-
65 trient and light availability (Lovenduski & Gruber, 2005; Boyd et al., 2008; Sallée et al.,
66 2010). For example, Lovenduski and Gruber (2005) regressed non-seasonal satellite chloro-
67 phyll anomalies onto the SAM index; their results suggest that SChl is positively cor-
68 related with the SAM south of the Polar Front (PF) due to increased iron supply by anoma-
69 lous upwelling, and negatively correlated with the SAM north of the PF due to stronger
70 light limitation stemming from deeper mixed layers.

71 While this type of analysis has helped discern mechanisms of non-seasonal SChl
72 variability (i.e. the variability that remains after removing the seasonal cycle), there are
73 limitations to this approach. First, using the SAM index as a measure of climate vari-
74 ability neglects significant regional differences in Southern Ocean winds, air-sea heat fluxes,
75 mixed-layer depth (MLD), and the MLD response to forcing (Sallée et al., 2010; Tam-

sitt et al., 2015; Rintoul, 2018; Keppler & Landschützer, 2019). Second, relating non-seasonal SChl variations to low-frequency climate modes presumes that high-frequency variability averages to near-zero on annual and longer timescales. However, many studies have documented large amplitude sub-seasonal SChl fluctuations throughout the global ocean (Bonhomme et al., 2007; Resplandy et al., 2009), and particularly in the Southern Ocean (Fauchereau et al., 2011; Joubert et al., 2014; Little et al., 2018). Therefore, here we investigate whether these transient processes imprint on the annual mean and year-to-year variations of Southern Ocean primary production (Little et al., 2018).

Following Keerthi et al. (2020), we decompose satellite-derived SChl into three frequency ranges: sub-seasonal (~ 0.5 -3 months), seasonal (~ 3 -12 months), and multi-annual (> 12 months). We show that there are distinct regional differences in the dominant timescale of SChl variability. For example, the seasonal cycle accounts for most of the variance in the subtropics, while non-seasonal variability dominates in most other parts of the Southern Ocean. This non-seasonal SChl variability primarily reflects sub-seasonal fluctuations, which occur over small spatial scales (~ 50 -150 km) and are not strongly correlated with the SAM. The importance of high-frequency events is related, in part, to the non-Gaussianity of chlorophyll. The multi-annual component of SChl, by contrast, is correlated with the SAM, but only explains about 10% of the total SChl variance across most of the Antarctic Circumpolar Current (ACC). This suggests that year-to-year variations in annual mean SChl are related to intermittency resulting from localized forcing such as storms and eddies, rather than low-frequency climate modes (Lévy et al., 2014). Consequently, the spatial scales associated with consistent variations in the annual mean are small (~ 100 -300 km), which implies that SChl should not be averaged over large regions to investigate year-to-year changes.

Complementary to satellite ocean color data, recent advances in autonomous observing platforms have dramatically increased the number of subsurface biogeochemical measurements in the Southern Ocean (Johnson et al., 2017; Talley et al., 2019). Fluorescence measurements from autonomous floats have shown good agreement with satellite-derived SChl products, and provide data under clouds and during polar night (Haëntjens et al., 2017). However, given the complex vertical structure of phytoplankton biomass in the Southern Ocean (Carranza et al., 2018; Uchida et al., 2019), fluctuations in SChl do not necessarily reflect changes in the vertically integrated chlorophyll column inventory (Chl_{tot}). Therefore, we also apply the same timeseries decomposition as we used

109 for the satellite data to float SCHl and Chl_{tot} to show that strong sub-seasonal variabil-
110 ity in SCHl is representative of the integrated signal. These results highlight the impor-
111 tance of small-scale processes in determining the annual mean SCHl and its variability.

112 **2 Data and Methods**

113 **2.1 Observational Datasets**

114 In this study, we use a merged SCHl data product from the European Space Agency
115 Ocean Color Climate Change Initiative (ESA OC-CCI) that combines data from mul-
116 tiple ocean color satellites (Sathyendranath et al., 2017) including Moderate Resolution
117 Imaging Spectroradiometer (MODIS), Sea-Viewing Wide Field-of-View Sensor (SeaWi-
118 FS), MEdium Resolution Imaging Spectrometer (MERIS) and Visible Infrared Imag-
119 ing Radiometer Suite (VIIRS). We use the Level 3 Mapped 25×25 km version at 8-day
120 temporal resolution, which spans 20 years from January 1999 to December 2018 and is
121 publicly available (<http://www.oceancolour.org/>). This merged data product captures
122 a longer time period than any individual satellite, and thus is well-suited for investiga-
123 tions of year-to-year variability. However, as with all ocean color products, there are many
124 data gaps in the Southern Ocean due to cloudiness, ice cover and low sun angles (Arrigo
125 et al., 2008). Locations with less than 50% data coverage over the full record are masked
126 out in this analysis, although we note that most of the missing data are from austral win-
127 ter when SCHl levels are near-zero due to light limitation.

128 To evaluate the relationship between temporal variability in SCHl and Chl_{tot} , we
129 also use in situ data from autonomous biogeochemical floats deployed by the Southern
130 Ocean and Climate Field Studies with Innovative Tools (SOCLIM) project. SOCLIM
131 floats measure temperature, salinity, pressure, dissolved oxygen, nitrate, fluorescence, backscat-
132 ter, and photosynthetically available radiation (Pellichero et al., 2020). Here, we ana-
133 lyze quality-controlled data from three SOCLIM floats (float IDs: 6902735, 6902736, 6902737)
134 that sampled in the Kerguelen Plateau region for three years, from September 2016 to
135 September 2019 (<http://soclim.com/>). These floats were selected since they are higher
136 resolution in time and depth than the standard biogeochemical Argo float (10-day cy-
137 cle time and 5 m resolution in the upper ocean). Data processing is described by Johnson
138 et al. (2017); the raw fluorometer data are transformed to engineering units using the
139 manufacturer calibration coefficients, the dark counts are adjusted using a gain correc-

140 tion, and the profiles are also corrected for nonphotochemical quenching following Xing
 141 et al. (2017). SOCLIM floats sampled unevenly in the vertical with roughly 1 m reso-
 142 lution in the upper ocean, and all profiles are linearly interpolated onto a regular depth
 143 axis with 5 m resolution. SChl is taken to be the average chlorophyll over the top 20 m,
 144 which is approximately the first optical depth (Morel, 1988). While Chl_{tot} is calculated
 145 as the vertical integral over the top 200 m of the water column (Grenier et al., 2015; von
 146 Berg et al., 2020), results are not sensitive to the precise integration depth. Floats also
 147 sampled unevenly in time, with profiles taken daily, every 2 days, and every 4 days at
 148 different points during the float lifetime. Here, we take 8-day means of the float data to
 149 match the temporal resolution of the satellite SChl product.

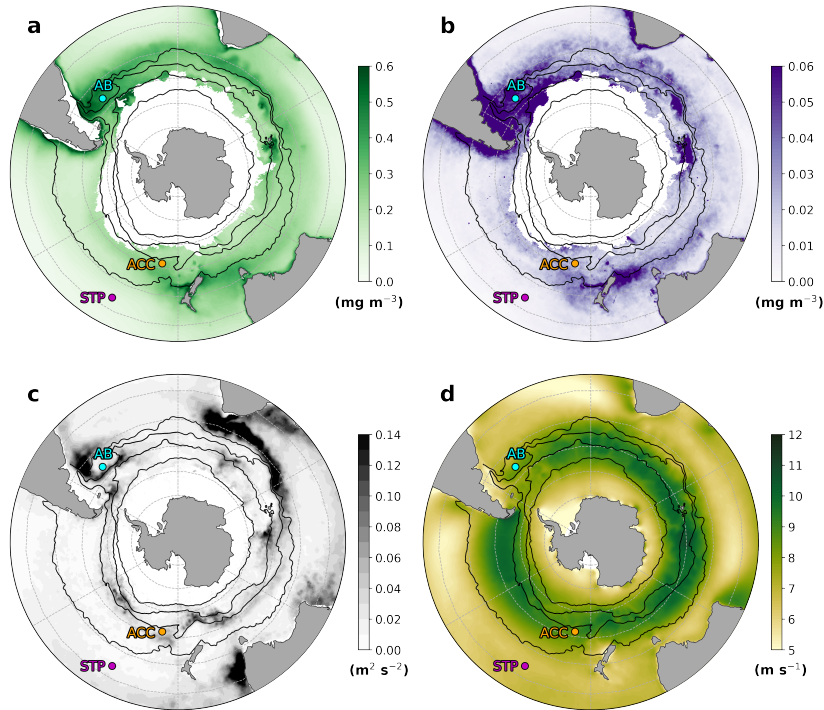


Figure 1. (a) 1999-2018 annual mean surface chlorophyll (mg/m^3) and (b) standard deviation of the annual mean (mg/m^3) from the ESA OC-CCI merged ocean color product. (c) 1979-2015 mean eddy kinetic energy (m^2/s^2) from surface drifters (Laurindo et al., 2017) (d) 1999-2018 summer (DJF) mean wind speed (m/s) from the CCMP merged data product. Colored points in all panels mark the stations whose timeseries are plotted in Figure 2: Subtropical Pacific (STP; magenta), ACC (orange), and Argentine Basin (AB; cyan). Black lines in all panels mark the mean position of the ACC fronts from Kim and Orsi (2014), which are from north to south: Subtropical front, Subantarctic front, Polar front, and Sea Ice Edge.

150 Wind data from the Cross-Calibrated Multi Platform (CCMP) product are used
 151 to examine some of the forcings that drive SChl variability. CCMP combines wind data

152 from several satellite scattermeters, moored buoys, and a reanalysis product (Atlas et
 153 al., 2011). CCMP winds have been shown to be more reliable at high frequencies than
 154 any single scattermeter, and have higher correlations with MLD than other wind prod-
 155 ucts (Atlas et al., 2011; Carranza & Gille, 2015). The merged wind product is available
 156 on the same 25×25 km horizontal grid as the SChl data from ESA OC-CCI. Here, we
 157 take 8-day means of the daily winds from 1999 to 2018 (i.e. the ESA OC-CCI period)
 158 to correspond directly with the ocean color data. The daily Antarctic Oscillation index
 159 (i.e. SAM index) from the NOAA/NCEP Climate Prediction Center from 1999 to 2018
 160 (<http://www.cpc.ncep.noaa.gov/>) was also averaged into 8-day periods to calculate cor-
 161 relations of different fields with the SAM.

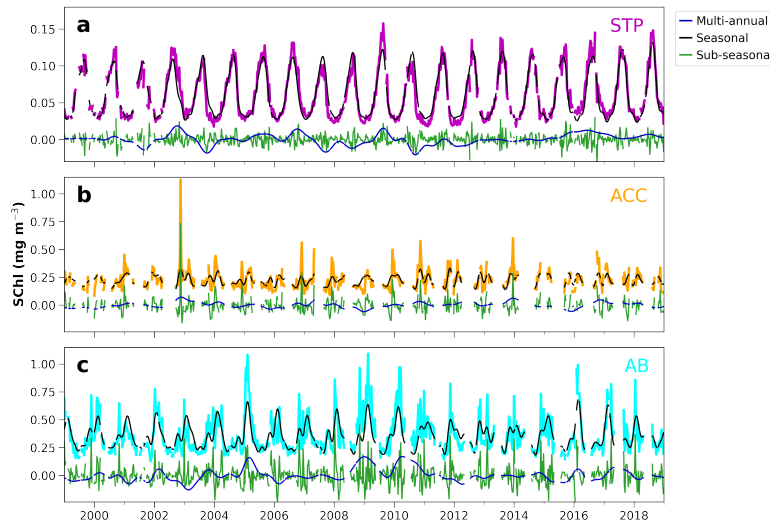


Figure 2. SChl timeseries decomposition for three stations marked in Figure 1: (a) Subtropical Pacific (34°S , 152°W), (b) Antarctic Circumpolar Current (52°S , 170°W), and (c) Argentine Basin (46°S , 45°W). The full signal (X_t) is plotted in (a) magenta, (b) orange, and (c) cyan. In all panels the multi-annual component (T_t) is blue, the seasonal component (S_t) is black, and the sub-seasonal component (I_t) is green.

162 2.2 Decomposition Method

163 Here, we decompose SChl timeseries at each grid point into three frequency bands
 164 following the method in Keerthi et al. (2020), which is based on the Census X11 iter-
 165 ative algorithm (Vantrepotte & Mélin, 2009). This decomposition uses a series of filters
 166 to separate the full SChl signal (X_t) into multi-annual (T_t), seasonal (S_t), and sub-seasonal
 167 (I_t) components such that $X_t = T_t + S_t + I_t$. The multi-annual component, T_t , is de-

168 terminated by a centered annual running mean and a Henderson filter of weight represent-
 169 ing one year, also applied iteratively. The seasonal component, S_t , captures variability
 170 with a period of ~ 3 -12 months and is isolated by taking multiple weighted running means
 171 over three consecutive timesteps and then applying an 88-day (i.e. approximately 3 months
 172 given the temporal resolution of the data) low-pass filter, iteratively. To account for year-
 173 to-year variations in the seasonal cycle, this decomposition method does not assume an
 174 annually repeating S_t . The sub-seasonal component, I_t , is found by applying a band-
 175 pass filter of 8-88 days. Finally, the residual is attributed to the sub-seasonal component,
 176 such that the timeseries is exactly decomposed into the sum of the three components.
 177 Note that this method does not have sharp frequency cut-offs in order to allow for vari-
 178 ations in the dominant period of the seasonal cycle and multiple harmonics in S_t . Fur-
 179 ther details of the decomposition method are provided in Keerthi et al. (2020). Figure
 180 2 illustrates the timeseries decomposition at three grid points whose locations are marked
 181 in Figure 1.

182 The total SCHl variance is partitioned into the sum of the variance in the multi-
 183 annual, seasonal, and sub-seasonal components, as well as the covariances between the
 184 terms: $\text{var}(X_t) = \text{var}(T_t) + \text{var}(S_t) + \text{var}(I_t) + 2\text{cov}(S_t, T_t, I_t)$. The covariance terms are small
 185 (explaining only a few percent of the total variance), so examining the individual vari-
 186 ances of T_t , S_t , and I_t directly quantifies the contribution of each frequency band to the
 187 total SCHl variance (Figure 3). We also estimate the spatial scales associated with each
 188 component of SCHl variability by cross-correlating T_t , S_t , and I_t at a given grid cell with
 189 the corresponding components at all other grid cells (Figure S1). From the number of
 190 cells where the correlation coefficient exceeds a threshold of 0.8, we then compute the
 191 area over which each signal remains consistent and take the length scale to be $\sqrt{\text{Area}}$.
 192 This threshold value was chosen following Keerthi et al. (2020), although the length scales
 193 are similar for a range of threshold values from 0.5 to 0.9 (Figure S2): namely, 200-400
 194 km, 500-600 km, 50-150 km for the multi-annual, seasonal, and sub-seasonal components,
 195 respectively.

196 **2.3 Synthetic Data**

197 In order to probe the statistical nature of the results, we also produced two syn-
 198 thetic timeseries with different probability distributions. Both artificial variables have
 199 red spectra, which are common for geophysical quantities, weighted toward low frequen-

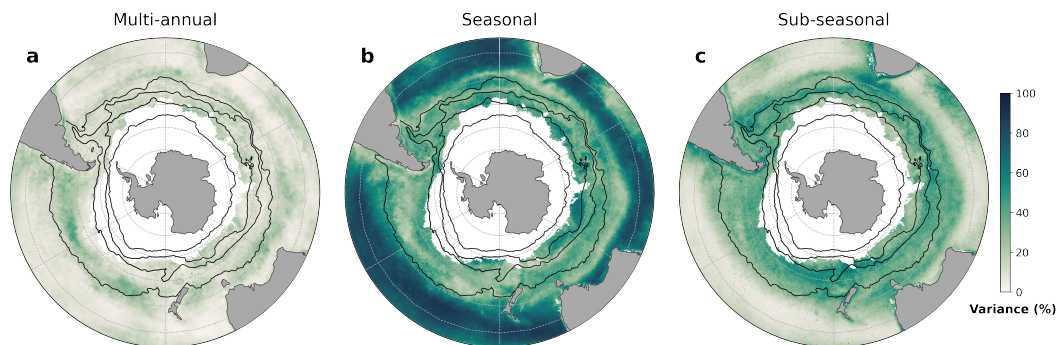


Figure 3. Percentage of the total SChl variance explained by the (a) multi-annual, (b) seasonal, and (c) sub-seasonal components of the SChl decomposition.

200 cies without a preferred period (Torrence & Compo, 1998; Maraun et al., 2007; Schulte
 201 et al., 2015). We generated red noise using an auto-regressive process with a lag-1 au-
 202 tocorrelation coefficient of 0.85, following Allen and Smith (1996). The first artificial vari-
 203 able is zero-mean with a Gaussian distribution (Figure 5a), which is representative of
 204 many normally distributed oceanic tracers. SChl, however, has been observed to follow
 205 a log-normal distribution; this is presumably because bio-optical properties in the ocean
 206 can be represented as the product of light attenuation coefficients, which would imply
 207 that SChl obeys the law of proportionate effect (Campbell, 1995). Therefore, our sec-
 208 ond artificial variable is taken to be the exponential of the first (Figure 5b), meaning that
 209 it is positive-valued and log-normally distributed, like SChl. We then apply the same de-
 210 composition method to the synthetic timeseries (Figure S3), although the three compo-
 211 nents simply represent high, mid, and low frequency bands since the timesteps are es-
 212 sentially arbitrary (i.e. the red noise cannot be interpreted as having sub-seasonal, sea-
 213 sonal, and multi-annual components). Comparing the results for the two synthetic vari-
 214 ables allows us to assess the extent to which the importance of sub-seasonal events to
 215 the total SChl variance stems from the log-normality of chlorophyll.

216 3 Results

217 3.1 Satellite Analysis

218 Southern Ocean primary production is heterogeneous in space and time. Still, dis-
 219 tinct bloom phenology regimes have been identified from satellite SChl, as well as large-
 220 scale patterns in the mean (Thomalla et al., 2011; Sallée et al., 2015; Ardyna et al., 2017).

221 Namely, higher annual mean SChl (Figure 1a) is observed in boundary current regions,
222 near fronts, and downstream of islands or topographic features in the path of the ACC
223 (Sokolov & Rintoul, 2007; Meredith et al., 2003; Rosso et al., 2016; Prend et al., 2019).
224 These patterns are related to heterogeneities in iron sources and the pathways that sup-
225 ply iron to the euphotic zone (Lancelot et al., 2009; Tagliabue et al., 2012; Graham et
226 al., 2015). There is also significant spatial variability in the standard deviation of the
227 annual mean (Figure 1b), which somewhat mirrors the structure in the annual mean it-
228 self (Figure S4). Year-to-year variations of SChl are larger within the ACC and in en-
229 energetic boundary currents with high EKE (Figure 1c). The subtropics (north of the Sub-
230 tropical front), by contrast, have low SChl values and less variability between years, which
231 coincides with weaker eddy activity and winds (Figure 1d).

232 Temporal SChl variability also demonstrates major regional differences, which is
233 illustrated by the timeseries in Figure 2. In the subtropics (Figure 2a), SChl resembles
234 a sinusoidal seasonal cycle with little change in amplitude between years, whereas in the
235 open ACC (Figure 2b), SChl fluctuations occurring on weekly timescales greatly exceed
236 the amplitude of the seasonal cycle. Finally, in boundary current regions such as the Brazil-
237 Malvinas confluence (Figure 2c), the seasonal cycle is more prominent than in the open
238 ACC (Figure 2b) but is punctuated by sub-seasonal pulses that significantly increase the
239 magnitude of the annual maximum. These regional patterns in the dominant timescale
240 of SChl variability lead to a fundamentally different interpretation of the annual mean
241 SChl value itself. For example, in the subtropics, where SChl is driven by seasonal vari-
242 ability, annual mean SChl reflects the integrated seasonal bloom. In contrast, in the open
243 ACC, where sub-seasonal variability dominates, annual mean SChl is manifested through
244 the sum of transient bursts that take place throughout spring and summer.

245 While the details of the timeseries plotted in Figure 2 are unique, we demonstrate
246 that these stations are representative of larger regional regimes by showing maps of the
247 percentage of total SChl variance explained by each frequency range (Figure 3). North
248 of the Subtropical front, the seasonal component explains >70% of the total variance (Fig-
249 ure 3b), consistent with the timeseries in Figure 2a. Moving southward into the ACC,
250 sub-seasonal variability is significantly stronger (Figure 3c), exceeding even the variance
251 explained by the seasonal cycle in many locations, such as the station shown in Figure
252 2b. This is consistent with Thomalla et al. (2011), who showed the greatest seasonal cy-
253 cle reproducibility in the subtropics. Across the entire Southern Ocean, the multi-annual

254 component is weak except in a narrow band spanning the Subantarctic Mode Water for-
 255 mation sites in the Pacific, where the deepest winter mixed layers in the entire South-
 256 ern Ocean are found (Hanawa & Talley, 2001). The comparatively large share of SChl
 257 variance explained by the multi-annual component in the mode water formation region
 258 may be due to the substantial variations in maximum winter MLD observed there, which
 259 have been linked to the SAM (Meijers et al., 2019) and could influence nutrient supply
 260 to the euphotic zone.

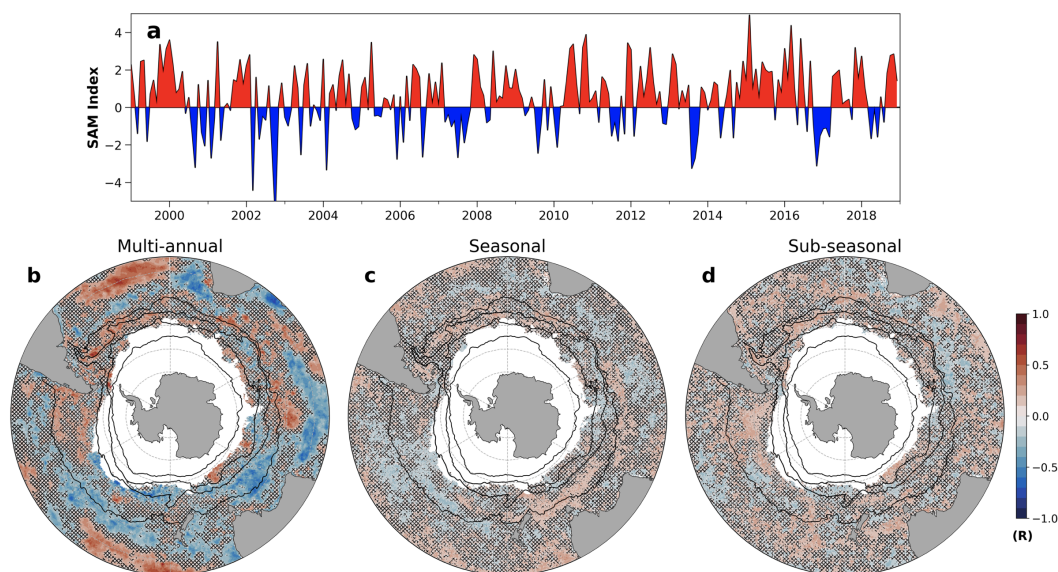


Figure 4. (a) 1999-2018 monthly SAM index from NOAA/NCEP Climate Prediction Center. (b-d) Correlation coefficient between the 8-day averages of the daily SAM index (to match the temporal resolution of the satellite SChl data) and the (b) multi-annual, (c) seasonal, and (d) sub-seasonal components of the SChl decomposition. In all panels, cross-hatching indicates where the correlations are not significant at the 95% level.

261 Non-seasonal SChl variability in the Southern Ocean is dominated by high-frequency
 262 rather than low-frequency fluctuations (Figure 3). Averaged across the entire ACC, sub-
 263 seasonal variations constitute 47% of the total SChl variance, and 81% of the non-seasonal
 264 SChl variance. This helps explain the relatively modest correlations between non-seasonal
 265 chlorophyll anomalies and the SAM index (Lovenduski & Gruber, 2005). To further ex-
 266 plore this, Figure 4 shows the correlation coefficients between the SAM index and each
 267 individual component of the SChl decomposition. The seasonal and sub-seasonal com-
 268 ponents of SChl are not strongly correlated with the SAM (Figure 4c,d). The multi-annual
 269 component, while much more highly correlated with the SAM (Figure 4b), only accounts

270 for about 10% of the total SChl variance (Figure 3a). The broad zonal pattern in Fig-
 271 ure 4b is consistent with results from Lovenduski and Gruber (2005). However, it is dif-
 272 ficult to extract a relationship between satellite SChl and the SAM because the low-frequency
 273 SChl variability associated with SAM forcing is overwhelmed by the much larger SChl
 274 fluctuations occurring at high frequencies.

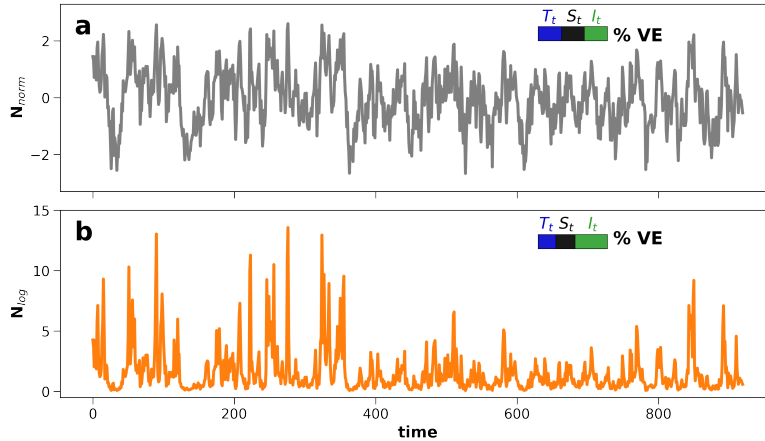


Figure 5. Synthetic timeseries of red noise generated by an auto-regressive process with (a) zero-mean and Gaussian distribution and (b) positive-valued and log-normal distribution. In both panels, insets show the percent variance explained (VE) by low (blue), mid (black), and high (green) frequency bands. These values are $T_t=33\%$, $S_t=32\%$, $I_t=34\%$ in (a), and $T_t=27\%$, $S_t=26\%$, $I_t=46\%$ in (b).

275 3.2 Synthetic Data Analysis

276 The large contribution of high frequencies to the total SChl variance could result
 277 from the non-Gaussianity of chlorophyll, since log-normally distributed variables (such
 278 as SChl) are known to be heavy tailed (Campbell, 1995). Therefore, synthetic timeseries
 279 (Figure 5) with varied probability distributions were used to assess this. Figure S3 gives
 280 the decomposition of the Gaussian and log-normal red noise, and the insets in Figure
 281 5 show the percent variance explained by high, mid, and low frequency bands. The zero-
 282 mean, Gaussian red noise has its variance evenly divided between the three components
 283 of the decomposition (inset in Figure 5a), whereas the positive-valued, log-normal red
 284 noise has a greater portion of its variance, 46%, explained by the high-frequency com-
 285 ponent (inset in Figure 5b). The sensitivity of these results to the details of the noise
 286 formulation have not been explored fully. Our intent is simply to demonstrate that the
 287 large magnitude of sub-seasonal SChl variability seen in the satellite data is connected,

288 in part, to its probability distribution, which lends more weight to extreme events due
 289 to its heavy tail. However, the partitioning of variance from the satellite SChl data does
 290 not appear to result solely from the log-normality of chlorophyll, since the same decom-
 291 position method applied to $\log(\text{SChl})$ also indicates a disproportionate importance of sub-
 292 seasonal variability (Figure S5).

293 3.3 Float Analysis

294 Given the sparsity of historical measurements in the Southern Ocean, remote sens-
 295 ing is an invaluable tool to study the region. However, satellite algorithms have been shown
 296 to underestimate SChl in the Southern Ocean compared to in situ measurements (Kahru
 297 & Mitchell, 2010). Furthermore, changes in SChl do not necessarily reflect changes in
 298 the integrated biomass (Carranza et al., 2018; Uchida et al., 2019). It is possible, for ex-
 299 ample, that sub-seasonal SChl variability is simply due to dilution of the surface signal
 300 by episodic mixing, rather than high-frequency changes in phytoplankton biomass. To
 301 assess this, we analyze subsurface data from three autonomous floats deployed near Ker-
 302 guelen Plateau by the SOCLIM project (Pellichero et al., 2020). Figure 6 shows the ver-
 303 tical chlorophyll section from float 6902735, as well as the comparison of SChl and Chl_{tot}
 304 timeseries.

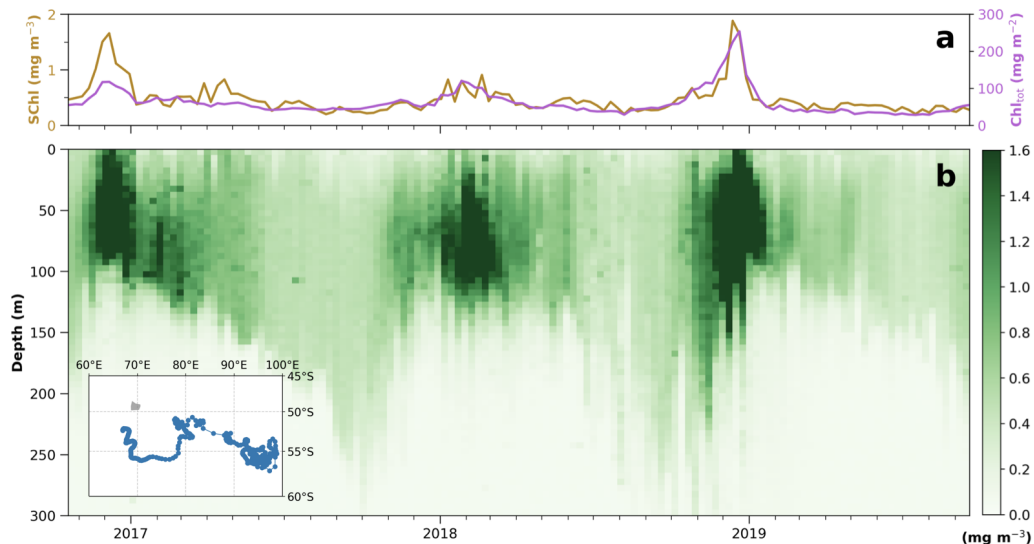


Figure 6. Float 6902735 (a) SChl (gold) and Chl_{tot} (purple) timeseries, as well as (b) vertical chlorophyll section with inlay showing float trajectory.

305 While much of the chlorophyll signal is subsurface, the SChl and Chl_{tot} timeseries
 306 are reasonably well correlated ($R=0.81$), albeit less so at sub-seasonal timescales ($R=0.66$).
 307 This was found by applying the same decomposition method outlined in Section 2.2 to
 308 float SChl and Chl_{tot} (Figure 7). For SChl, the percentages of variance explained by the
 309 multi-annual, seasonal, and sub-seasonal components are 9%, 46%, and 44%, respectively,
 310 while for Chl_{tot}, the percentages of variance explained by the multi-annual, seasonal, and
 311 sub-seasonal components are 8%, 55%, and 36%, respectively. In other words, sub-seasonal
 312 variability is stronger for SChl compared to Chl_{tot}, which implies larger variations in bi-
 313 ological rates and concentrations near the surface than at depth. This could be, in part,
 314 due to dilution of the surface signal rather than changes in total biomass. Although, sub-
 315 seasonal Chl_{tot} variability still contributes a large share to the total variance and exceeds
 316 the multi-annual component, as we see for SChl. The same conclusion was drawn from
 317 the other two SOCLIM floats analyzed (floats IDs: 6902736 and 6902737); analogous plots
 318 are shown in the Supporting Information (Figures S6-S9). This suggests that the results
 319 based on satellite SChl data (Section 3.1) are relevant to the vertically integrated chloro-
 320 phyll, although possibly slightly overestimating the contribution of sub-seasonal timescales
 321 to the total variability.

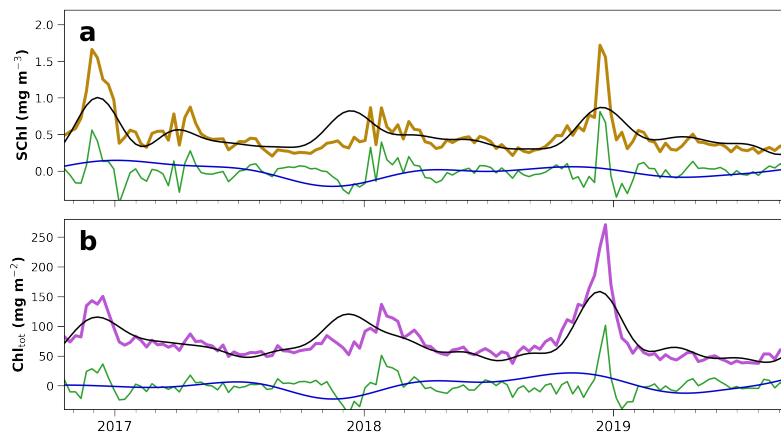


Figure 7. Timeseries decomposition of float 6902735 (a) SChl, full signal in gold, and (b) Chl_{tot}, full signal in purple. In both panels the multi-annual component is blue, the seasonal component is black, and the sub-seasonal component is green.

4 Discussion and Conclusions

Satellite data and autonomous float measurements analyzed here show that sub-seasonal SChl variability exceeds multi-annual variability in the Southern Ocean. As a result, year-to-year variations of annual mean SChl primarily reflect high-frequency events rather than low-frequency variability (Little et al., 2018). This is because, within the ACC, the annual mean SChl value itself results from the sum of intermittent pulses occurring at weekly timescales (or at shorter timescales not resolved by the satellite dataset). Therefore, the annual mean SChl is higher in years with more or larger pulses, which is confirmed by high correlations between annual mean SChl and annual variance of the sub-seasonal component of SChl (Figure 8a). The inverse cascade toward low frequencies could result from ecological fluctuations or from changes in the prevalence of extreme wind events or eddy activity (Cravatte et al., 2021), which in turn may be connected to climate variability (Busecke & Abernathy, 2019; Hell et al., 2021), although sub-seasonal SChl variations were only weakly correlated with the SAM index (Figure 4d).

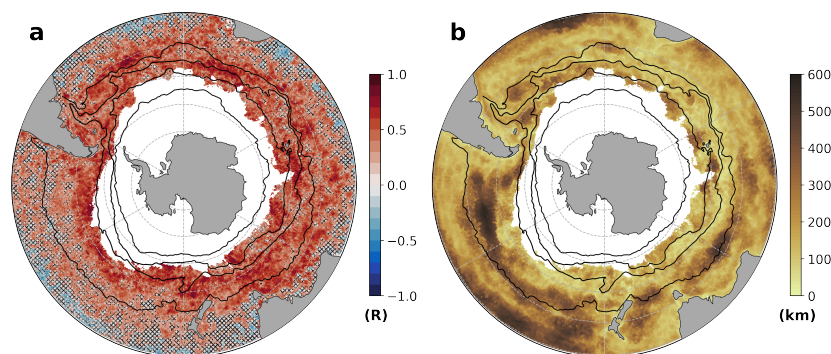


Figure 8. (a) Correlation coefficient between annual mean SChl and annual variance in the sub-seasonal component of SChl. Cross-hatching indicates where the correlations are not significant at the 95% level. (b) Length scale (km) associated with consistent variations in annual mean SChl.

The link between annual mean SChl and high-frequency events is important because sub-seasonal SChl variability occurs at spatial scales of ~ 50 - 150 km (Figure S1c), which leads to a similarly small spatial autocorrelation for variations in annual mean SChl (Figure 8b). In the ACC, the average length scale associated with correlated fluctuations in annual mean SChl is only 260 km. This is in contrast to the seasonal cycle of SChl, which is forced, to leading order, by large-scale changes in solar irradiance and surface stratification, and thus has much larger spatial scales, ~ 600 km (Figure S1b). For ex-

343 ample, vast bloom phenology regimes have been defined based on SChl seasonality, and
 344 approximately correspond to the frontal zones of the ACC (Thomalla et al., 2011; Sallée
 345 et al., 2015; Ardyna et al., 2017). Indeed, averaging the satellite data over the Subtrop-
 346 ical Zone (STZ), Subantarctic Zone (SAZ), and the ACC—as defined by the mean frontal
 347 positions from Kim & Orsi (2014), see Supporting Information—shows that, in a given
 348 frontal zone, the seasonal component of SChl (S_t) has a small standard error (Figure 9a);
 349 this means that the seasonal cycle is relatively consistent across all grid cells, although
 350 note that the calculation of standard error assumes Gaussian statistics. However, the
 351 full SChl signal (X_t) has larger standard errors within a frontal zone (Figure 9b), par-
 352 ticularly in the SAZ and ACC where sub-seasonal variability is strong. This is also re-
 353 flected in the fluctuations of annual mean SChl, which have large standard errors in the
 354 SAZ and in the ACC (Figure 9c), despite the regularity of the seasonal cycle over these
 355 zones. In other words, the bioregions defined based on phytoplankton seasonality or time-
 356 mean SChl are not necessarily meaningful in the context of year-to-year variations.

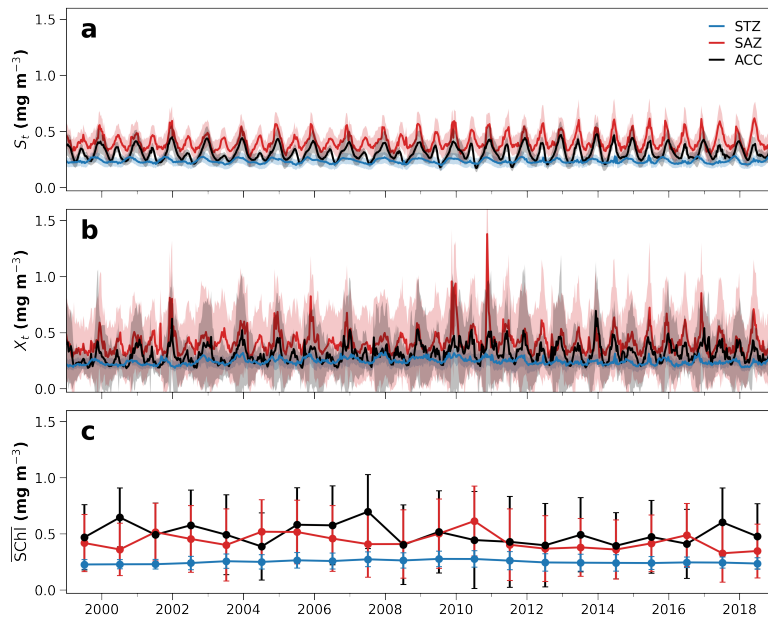


Figure 9. (a) Seasonal component of SChl (S_t) averaged over the Subtropical Zone (STZ), Subantarctic Zone (SAZ), and ACC, as defined by the Kim & Orsi (2014) fronts. (b) Full SChl signal (X_t) averaged over the same frontal zones as in (a). (c) Annual mean SChl ($\overline{\text{SChl}}$) for each frontal zone plotted at the mid-point of each respective year (i.e. July 2). Error bars reflect the standard error of all grid cells within each frontal zone.

357 These results suggest that changes in annual mean SCHl are tied to the forcing that
358 drives sub-seasonal SCHl fluctuations. This includes anomalies in wind stress or surface
359 buoyancy forcing (Swart et al., 2015; Carranza & Gille, 2015; Keerthi et al., 2021), oceanic
360 mesoscale and sub-mesoscale variability (Frenger et al., 2018; Whitt, Lévy, & Taylor, 2019;
361 McGillicuddy, 2016), or ecosystem interactions such as top-down controls from grazing
362 (Behrenfeld & Boss, 2014; Arteaga et al., 2020), competition for multiple resources (Huisman
363 & Weissing, 2001), and interactions between the two (Mayersohn et al., 2021). It is dif-
364 ficult to separate the effects of these mechanisms for several reasons. First, the timescales
365 associated with mesoscale and submesoscale physical processes overlap with those of in-
366 trinsic ecosystem variability. Second, the sign of the SCHl response to wind or MLD per-
367 turbations exhibits significant seasonal and regional variability (Le Quéré et al., 2002;
368 Llort et al., 2019). For example, several studies have observed a seasonal progression from
369 light limitation to nutrient limitation in the Southern Ocean (Ryan-Keogh et al., 2018;
370 von Berg et al., 2020; Li et al., 2021). In a light-limited regime, phytoplankton growth
371 is associated with restratification due to decreased winds and/or submesoscale buoyancy
372 fluxes (Swart et al., 2015; Thomalla et al., 2015; du Plessis et al., 2017; Pellichero et al.,
373 2020). In contrast, in a nutrient-limited regime, increases in SCHl are driven by transient
374 nutrient entrainment from storm-driven mixing (Carranza & Gille, 2015), eddy activ-
375 ity (Uchida et al., 2020), or wind-eddy interactions (Gille et al., 2014; du Plessis et al.,
376 2019).

377 Untangling these mechanisms has important implications for year-to-year variabil-
378 ity. For example, if sub-seasonal SCHl fluctuations are driven primarily by wind-driven
379 nutrient entrainment from synoptic storms, then annual mean SCHl could presumably
380 be linked to storm frequency. In contrast, if sub-seasonal SCHl fluctuations are forced
381 by oceanic (sub-)mesoscale variability, then annual mean SCHl would possibly be connected
382 to changes in EKE. Finally, some studies suggest that the surface iron supply is set by
383 wintertime mixing (Tagliabue et al., 2014; Nicholson et al., 2019), in which case annual
384 mean SCHl would potentially be related to the previous winter’s maximum MLD. Test-
385 ing these hypotheses is difficult using observations. We tried, for example, to correlate
386 annual mean SCHl with summer storm frequency (Figure S10), defined as the percent-
387 age of days in summer (DJF) with daily mean wind speed greater than 10 m/s (Carranza
388 et al., 2018). The correlations are relatively modest, but this could be due to inaccuracy
389 in the wind product at high frequencies, decoupling in time between mixing and wind

390 stress at sub-seasonal timescales (Whitt et al., 2017), the nonlinear relationship between
391 MLD and surface forcing (Whitt, Nicholson, & Carranza, 2019), or variability in the phy-
392 toplankton response to MLD perturbations (Llort et al., 2019). Other studies (e.g. Li
393 et al., 2021) have additionally shown a weak relationship between annual mean produc-
394 tion and MLD. However, further work is needed to quantify the contribution of these dif-
395 ferent processes to the total year-to-year variability.

396 While many previous studies have examined sub-seasonal SChl variability and have
397 highlighted the complex mechanisms at play, the role of high-frequency fluctuations in
398 driving the annual mean SChl and its variability is not widely recognized. Non-seasonal
399 SChl variability in the Southern Ocean has often been attributed to the SAM (Lovenduski
400 & Gruber, 2005; Greaves et al., 2020). However, here we have shown that low-frequency
401 SChl fluctuations, which show a relationship to the SAM index, are dwarfed by the much
402 larger amplitude sub-seasonal variability. Therefore, year-to-year changes in annual mean
403 SChl reflect episodic forcing, such as storms and eddies, rather than multi-annual cli-
404 mate variability. Although future work should investigate the role of climate modes in
405 modulating the prevalence and magnitude of synoptic events and (sub-)mesoscale mix-
406 ing (Busecke & Abernathey, 2019; Hell et al., 2021). One implication of these results is
407 that annual mean SChl only varies consistently over small spatial scales. Consequently,
408 developing a mechanistic understanding of year-to-year variations in Southern Ocean pri-
409 mary production is an inherently local question that requires resolving sub-seasonal, small-
410 scale processes.

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421 CCMP product are available online (<http://www.remss.com/measurements/ccmp/>). The

422 daily Antarctic Oscillation index is available from the NOAA/NCEP Climate Predic-
423 tion Center (<http://www.cpc.ncep.noaa.gov/>). Mean EKE is calculated from a NOAA
424 surface drifter climatology (http://www.aoml.noaa.gov/phod/gdp/mean_tvelocity.php).

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